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Benchmarking LLMs in Political Content Text-Annotation

Proof-of-Concept with Toxicity and Incivility Data

Bastián González-Bustamante
Leiden University & Universidad Diego Portales
✉ b.a.gonzalez.bustamante@fgga.leidenuniv.nl

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Introduction

The Challenge of Online Toxicity

Digital platforms and incivility. The rise of digital platforms has seen a surge in incivility and toxicity in online interactions, particularly in political discussions.

Need for automated solutions. The sheer volume of online content makes manual annotation impractical, necessitating automated solutions for analysing toxicity and incivility.

LLMs as a potential solution. LLMs offer a promising avenue for automating the annotation process, potentially revolutionising how we study online political discourse.

Introducing LLMs to the Field

Traditional text analysis. Traditional approaches to analysing text data in social sciences often relied on manual coding, dictionaries, or topic modelling, which can be time-consuming and resource-intensive.

The power of LLMs. LLMs, with their zero- and few-shot learning capabilities, offer a powerful alternative, enabling researchers to process and analyse vast amounts of text data efficiently.

Transforming research. This shift towards AI-powered analysis has the potential to transform computational social science research, particularly in understanding online toxicity and incivility.

OpenAI's GPTs: A Closer Look

GPT and research

Researchers have increasingly utilised OpenAI's GPT models through their **API for various tasks**, including text annotation and classification.

Advantages of GPT models

GPT models offer several advantages, including **ease of use**, access to substantial computational resources, and **impressive performance** in many tasks.

Concerns and limitations

However, concerns remain regarding **reproducibility**, data privacy, and the potential for bias in these proprietary models.

The Rise of Open-Source LLMs

Addressing the limitations

Open-source LLMs have emerged as a response to concerns surrounding proprietary models, emphasising transparency, **reproducibility**, and community-driven development.

Performance and potential

Recent studies have shown that open-source LLMs can match or **even surpass** the performance of proprietary models in specific text annotation tasks, particularly in zero-shot classification.

Cost-effective alternatives

Some open-source "Small Language Models" (SLMs) offer comparable performance with significantly **reduced computational requirements** and costs.

Data and Methods

Data and Gold Standard

Novel dataset on protest events

Protests against the coronavirus and judicial reform (August 2020) ✔

Social outburst in Chile (October 2019) ✔

Protests against education budget cuts (May 2019) ✖

∼3.5M messages in total*

* ∼5M including Brazil

LLMs zero-shot classification

› Random, balanced sample of **1,000 messages**

Open-source LLMs deployed locally

› Minimum temperature to ensure reproducibility**

Intel Core i9-14900K CPU

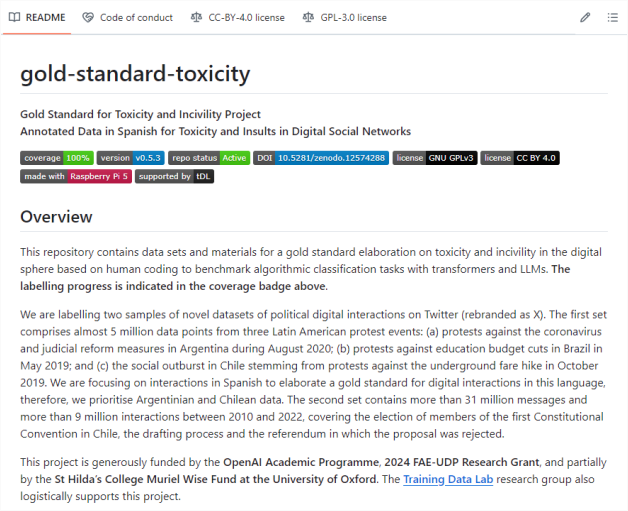
NVIDIA GeForce RTX 4070 Super Windforce OC 12GB GPU

64 GB of RAM (DDR5-4800)

Windows Subsystem for Linux v2.1.5.0 and Ollama v0.3.10 and v0.3.12

** We ran some temperature experiments to test models' hallucinations and reproducibility.

Gold Standard



README | Code of conduct | CC-BY-4.0 license | GPL-3.0 license

gold-standard-toxicity

Gold Standard for Toxicity and Incivility Project
Annotated Data in Spanish for Toxicity and Insults in Digital Social Networks

coverage 100% | version v0.5.3 | repo status Active | DOI 10.5281/zenodo.12574288 | license GNU GPLv3 | license CC BY 4.0
made with Raspberry Pi 5 | supported by tDL

Overview

This repository contains data sets and materials for a gold standard elaboration on toxicity and incivility in the digital sphere based on human coding to benchmark algorithmic classification tasks with transformers and LLMs. **The labelling progress is indicated in the coverage badge above.**

We are labelling two samples of novel datasets of political digital interactions on Twitter (rebranded as X). The first set comprises almost 5 million data points from three Latin American protest events: (a) protests against the coronavirus and judicial reform measures in Argentina during August 2020; (b) protests against education budget cuts in Brazil in May 2019; and (c) the social outburst in Chile stemming from protests against the underground fare hike in October 2019. We are focusing on interactions in Spanish to elaborate a gold standard for digital interactions in this language, therefore, we prioritise Argentinian and Chilean data. The second set contains more than 31 million messages and more than 9 million interactions between 2010 and 2022, covering the election of members of the first Constitutional Convention in Chile, the drafting process and the referendum in which the proposal was rejected.

This project is generously funded by the **OpenAI Academic Programme**, **2024 FAE-UDP Research Grant**, and partially by the **St Hilda's College Muriel Wise Fund at the University of Oxford**. The Training Data Lab research group also logistically supports this project.

The sample was manually annotated by a team of five high-skilled human coders on Labelbox.

Each message was hand-coded by two different coders of the team, therefore, we have **two ground-truth labels for each sample observation**.

GitHub repository.

Gold Standard

We used a binary codification performed using the core definitions of Perspective for toxicity as follows:

Human annotation

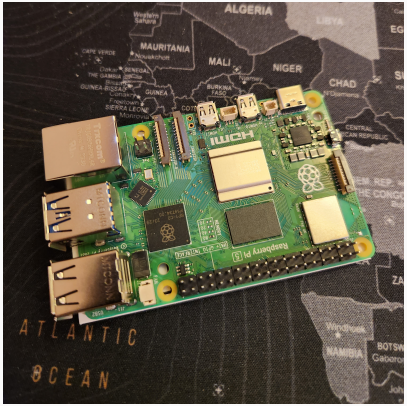
Classify the category of the comment as either **TOXIC** or **NONTOXIC**. **TOXIC:** Rude, disrespectful, or unreasonable comments that are likely to make someone leave the discussion or stop sharing their perspective. **NONTOXIC:** Civil or nice comments that are unlikely to discourage conversation.

- Krippendorff's α (bootstrap 1,000x) 0.944 (95% CI [0.919, 0.961]).
- The process involved 7.2 hours of annotation and 1.2 hours of revision.

Perspective API Classification on Raspberry Pi 5

First, we ran Perspective API, a distilled BERT developed by Jigsaw and Google. The classification implied **2,411 hours** of computing **(entire dataset, not only the sample)**.

The process was deployed on a **Raspberry Pi 5**, a small computer board with an ARM CPU and meagre power consumption. Our footprint using Raspberry Pi 5 was 6.51 kg of CO2, which implied a **reduction of 96% in emissions** that we would have generated running the tasks on an average cloud computing service.



* Picture of the Raspberry Pi 5 used for classification.

LLMs for Text-Annotation: Prompt Strategy

Our prompt strategy was the very **same used on the human annotation** based on the core definitions of Perspective and Google for toxicity with the following system message:

System message

Classify the category of the comment as either **TOXIC** or **NONTOXIC**. **TOXIC:** Rude, disrespectful, or unreasonable comments that are likely to make someone leave the discussion or stop sharing their perspective. **NONTOXIC:** Civil or nice comments that are unlikely to discourage conversation.

Along with providing texts of our balanced sample, we also listed the categories for the task as follows: **"Respond with only the category (TOXIC or NONTOXIC). Do not provide any additional analysis or explanation."**

Results

Running Cycle 1: Baseline

Benchmarking LLMs in Political Content Text-Annotation

* o1-preview and o1-mini, released recently on September 12, 2024, are not fully available to all API users.

OpenAI's GPTs*

GPT-4o (2024-05-13), GPT-4o mini, GPT-4, GPT-4 Turbo and GPT-3.5 Turbo

SOTA open-source LLMs

Llama 3.1 (8B), Hermes 3 (8B), Gemma 2 (9, 27B) and Mistral NeMo (12B)

Slightly outdated open-source LLMs

Nous Hermes 2 Mixtral (47B), Nous Hermes 2 (11B), Mistral OpenOrca (7B), Orca 2 (7B) and Aya (35B)

Benchmarking Cycle 1: Baseline

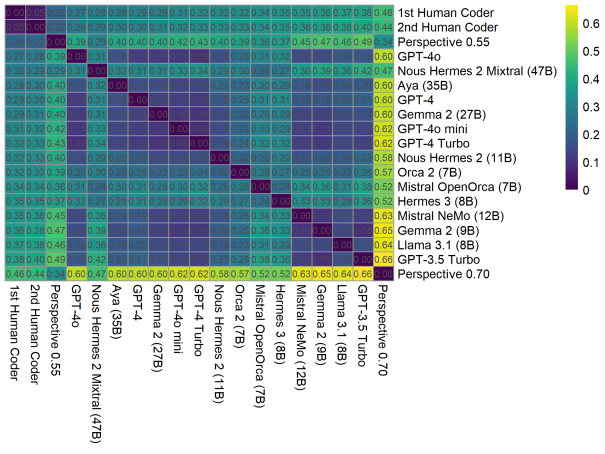
Model	Accuracy	Precision	Recall	F1-Score
Perspective 0.55	0.882	0.975	0.800	0.879
GPT-4o (2024-05-13)	0.804	0.735	0.991	0.844
Nous Hermes 2 Mixtral (47B)	0.829	0.859	0.813	0.835
Aya (35B)	0.793	0.727	0.979	0.835
GPT-4 (0613)	0.793	0.737	0.953	0.831
Gemma 2 (27B)	0.785	0.719	0.979	0.830
GPT-4o mini (2024-07-18)	0.761	0.695	0.985	0.815
GPT-4 Turbo (2024-04-09)	0.757	0.690	0.989	0.813
Nous Hermes 2 (11B)	0.772	0.727	0.918	0.811
Orca 2 (7B)	0.773	0.740	0.888	0.807
Mistral OpenOrca (7B)	0.777	0.790	0.794	0.792
Hermes 3 (8B)	0.770	0.771	0.811	0.790
Mistral NeMo (12B)	0.717	0.659	0.976	0.786
Gemma 2 (9B)	0.697	0.639	0.993	0.778
Llama 3.1 (8B)	0.706	0.659	0.931	0.772
GPT-3.5 Turbo (0125)	0.667	0.616	0.998	0.762
Perspective 0.70	0.756	1.000	0.543	0.704

F1-Score under 0.80

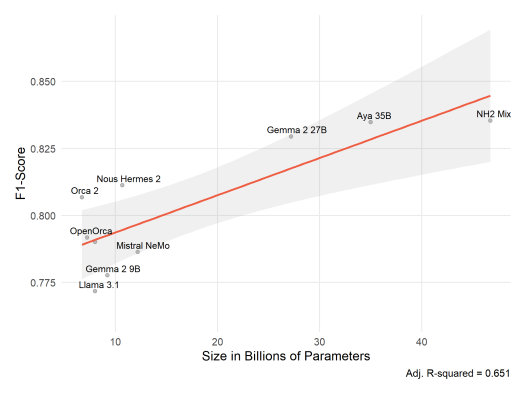
Jaccard Distance between Gold Standard and Classifiers

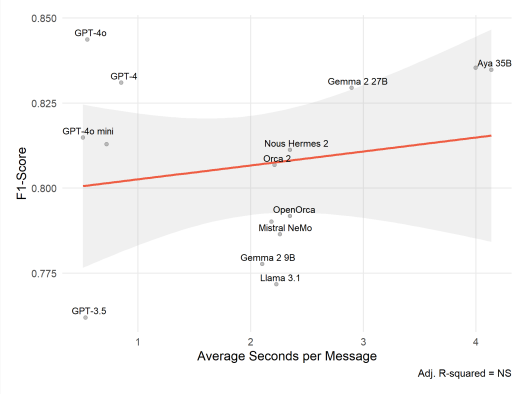
With an intermediate performance, **Mistral OpenOrca** and **Hermes 3**, both with parameters between 7 and 8B, show indexes around 0.30, therefore, they are not highly similar to other models. This could open avenues for ensemble annotations or stacking.

The same applies to Nous Hermes 2 Mixtral, which showed one of the highest performances.

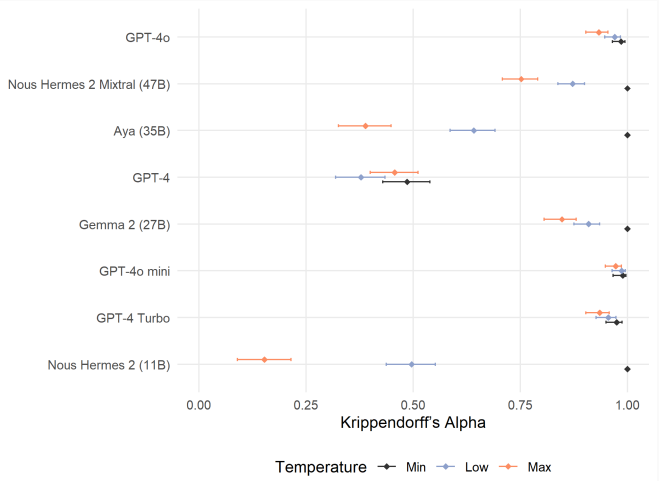


Performance, Parameters and Computing Time





Computing Time vs Reproducibility



Time per obs.

Human coder: 15.125s

Perspective API: 1.175s

OpenAI's GPTs: 0.633s

Open-source LLMs: 2.672s

How much faster than humans?

Open-source LLMs ∼6x

Perspective API ∼13x

OpenAI's GPTs ∼24x

Step Back: ML and Transformers

ML classification models

Naïve Bayes, SVM kernel-based linear, Random Forest with 100 and 500 and XGBoost

Hyperparameters tuning

Additive smoothing, regularisation, limiting depth to control for overfitting, internal nodes and learning rate

Fine-tuned BERT-ish models

ft RoBERTa (base on ∼58M tweets)
ft XML-RoBERTa (base on 2.5TB multilingual data)
ft BERT Spanish (base BERT model for Spanish)

Step Back: ML and Transformers (Top-15)

Model	Accuracy	Precision	Recall	F1-Score
Perspective 0.55	0.882	0.975	0.800	0.879
ft BERT Spanish⋆	0.835	0.816	0.886	0.849
GPT-4o (2024-05-13)	0.804	0.735	0.991	0.844
Nous Hermes 2 Mixtral (47B)	0.829	0.859	0.813	0.835
Aya (35B)	0.793	0.727	0.979	0.835
GPT-4 (0613)	0.793	0.737	0.953	0.831
Gemma 2 (27B)	0.785	0.719	0.979	0.830
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Nous Hermes 2 (11B)	0.772	0.727	0.918	0.811
Orca 2 (7B)	0.773	0.740	0.888	0.807
Mistral OpenOrca (7B)	0.777	0.790	0.794	0.792
Naïve Bayes⋆	0.730	0.708	0.895	0.791
Hermes 3 (8B)	0.770	0.771	0.811	0.790
ft XML-roBERTa⋆	0.740	0.688	0.924	0.789

Rookie in the cycle; **F1-Score under 0.80**; ⋆20% validation set, expected decrease in *pseudo*-test set

Running Cycle 2: SOTA LLMs

OpenAI's GPTs

GPT-4o (2024-08-06)

SOTA open-source LLMs

Llama 3.1 (70, 405B), Hermes 3 (70B), Aya Expanse (8, 32B), Qwen 2.5 (7, 14, 32, 72B), Mistral Small (22B) and Solar Pro (22B)

Additional thresholds for Perspective

Perspective 0.60 and 0.80

Benchmarking Cycle 2: SOTA LLMs (Top-15)

Model	Accuracy	Precision	Recall	F1-Score
Perspective 0.55	0.882	0.975	0.800	0.879
Qwen 2.5 (32B)	0.823	0.763	0.970	0.854
Perspective 0.60	0.862	0.995	0.745	0.852
GPT-4o (2024-05-13)	0.804	0.735	0.991	0.844
GPT-4o (2024-08-06)	0.802	0.735	0.985	0.842
Qwen 2.5 (72B)	0.804	0.741	0.972	0.841
Aya Expanse (32B)	0.804	0.748	0.955	0.839
Llama 3.1 (405B)	0.840	0.912	0.775	0.838
Hermes 3 (70B)	0.808	0.769	0.916	0.836
Nous Hermes 2 Mixtral (47B)	0.829	0.859	0.813	0.835
Aya (35B)	0.793	0.727	0.979	0.835
GPT-4 (0613)	0.793	0.737	0.953	0.831
Gemma 2 (27B)	0.785	0.719	0.979	0.830
Qwen 2.5 (14B)	0.799	0.756	0.921	0.830
Qwen 2.5 (7B)	0.776	0.727	0.929	0.816

Rookie in the cycle

Cycle 3: Fine-tuning LLMs

ft GPT-4o

- Base GPT-4o (2024-08-06 ∼200B)
- ft AOnla1B3
- 625,410 tokens
- 5 epochs
- Training loss 0.060
- API deployable ☑

ft Mistral (7B)

- Base Open Mistral (7B)
- ft 328207d0
- 1,310,720 tokens
- 8.563 epochs
- Training loss 0.081
- API deployable ☑

ft Mistral (123B)

- Base Mistral Large (123B)
- ft cbaac529
- 1,530,610 tokens
- 10 epochs
- Training loss 0.078
- API deployable ☑

Benchmarking Cycle 3: Fine-tuning LLMs (Top-15)

Model	Accuracy	Precision	Recall	F1-Score
ft GPT-4o⋆	0.874	0.882	0.931	0.906
ft Mistral (123B)⋆	0.847	0.849	0.931	0.888
Perspective 0.55	0.882	0.975	0.800	0.879
Qwen 2.5 (32B)	0.823	0.763	0.970	0.854
Perspective 0.60	0.862	0.995	0.745	0.852
GPT-4o (2024-05-13)	0.804	0.735	0.991	0.844
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GPT-4 (0613)	0.793	0.737	0.953	0.831
Gemma 2 (27B)	0.785	0.719	0.979	0.830

Rookie in the cycle; ⋆ *pseudo*-test set

Extended Benchmarking Overview (Top-15)

Model	Accuracy	Precision	Recall	F1-Score	Deploy	CO_2
ft GPT-4o*	0.874	0.882	0.931	0.906	API	🏭
ft Mistral (123B)*	0.847	0.849	0.931	0.888	API	🏭
Perspective 0.55	0.882	0.975	0.800	0.879	API-RPi5	🍃
Qwen 2.5 (32B)	0.823	0.763	0.970	0.854	Local	⚖️
Perspective 0.60	0.862	0.995	0.745	0.852	API-RPi5	🍃
GPT-4o (2024-05-13)	0.804	0.735	0.991	0.844	API	🏭
GPT-4o (2024-08-06)	0.802	0.735	0.985	0.842	API	🏭
Qwen 2.5 (72B)	0.804	0.741	0.972	0.841	Local	⚖️
Aya Expanse (32B)	0.804	0.748	0.955	0.839	Local	⚖️
Llama 3.1 (405B)	0.840	0.912	0.775	0.838	API	🏭
Hermes 3 (70B)	0.808	0.769	0.916	0.836	Local	⚖️
Nous Hermes 2 Mixtral (47B)	0.829	0.859	0.813	0.835	Local	⚖️
Aya (35B)	0.793	0.727	0.979	0.835	Local	⚖️
GPT-4 (0613)	0.793	0.737	0.953	0.831	API	🏭
Gemma 2 (27B)	0.785	0.719	0.979	0.830	Local	⚖️

Private-closed; **Open-source**; **BERT-ish**; * *psuedo*-test set

Error Rate vs 2nd Human Coder

Predictive Performance Index (PPI). Average performance metrics with equal weights.

Geometric Mean (GPI). Penalty on low values controlling volatility between metrics using the 4th root of the product of performance metrics.

Misclassification			PPI	GPI
Top-Tier Options				
ft GPT-4o	vs	2nd Coder	7.50%	7.52%
ft Mistral (123B)	vs	2nd Coder	9.45%	9.51%
Perspective 0.55	vs	2nd Coder	8.93%	9.14%
Mid-Range Option				
Orca 2 (7B)	vs	2nd Coder	17.13%	17.31%
Sub-Optimal Options				
GPT-3.5 Turbo	vs	2nd Coder	21.25%	22.56%
Perspective 0.80	vs	2nd Coder	32.68%	36.58%

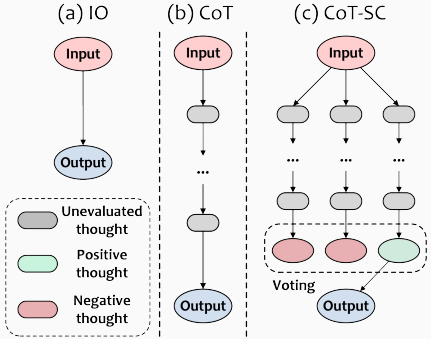
Private-closed; Open-source; BERT-ish

Chain-of-Thought and Self-Consistency

Model	Prompting	Variation	
		PPI	GPI
GPT-4o	CoT-SC	3.84%	4.18%
GPT-4o	CoT	3.18%	3.47%
Qwen2.5 (32B)	CoT-SC*	1.38%	1.53%
Qwen2.5 (32B)	CoT*	1.29%	1.44%
ft GPT-4o	CoT-SC	0.17%	0.18%
ft GPT-4o	CoT	0.14%	0.16%
ft Mistral (123B)	CoT-SC*	−1.34%	−1.57%
ft Mistral (123B)	CoT*	−1.59%	−1.85%

Private-closed; Open-source

*About 15% of outcome need more cleaning because of JSON issues.



Source: Din et al. (2024).

Takeaways

Takeaways

🏆 **Fine-tuned GPT-4o** and **Mistral (123B)** outperform other LLM's zero-shot classification. **Perspective API** using a laxer threshold still shows an outstanding performance.

⚠ Classic machine learning approaches and even fine-tuned BERT-ish models are **not competitive against LLMs**.

⚠ Sub-optimal choices could lead to **misclassification above 20%**.

☑ Although GPTs tend to show not only excellent computing time but also overall good levels of reliability, **only open-source LLMs ensure full reproducibility** in the annotation.

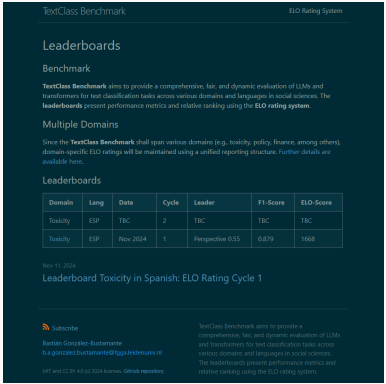
☑ **CoT shows a slight improvement**, ∼1-2%, and it seems to work better in unfine-tuned models. The JSON structure could be problematic, and there is an important increase in computing time.

TextClass Benchmark

TextClass Benchmark aims to provide a comprehensive, fair, and dynamic evaluation of LLMs and transformers for text classification tasks across various domains and languages in social sciences.

The leaderboards present performance metrics and relative ranking using the **Elo rating system**.

textclass-benchmark.com



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Thank you very much!

Do you have any questions?

b.a.gonzalez.bustamante@fgga.leidenuniv.nl

bgonzalezbustamante.com

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